THE UNIVERSITY *of York*

Discussion Papers in Economics

No. 2003/09

Total Factor Productivity Growth, Technical Efficiency Change and Energy Input. An International Frontier Analysis

by

Luis R Murillo-Zamorano

Department of Economics and Related Studies
University of York
Heslington
York, YO10 5DD

TOTAL FACTOR PRODUCTIVITY GROWTH, TECHNICAL EFFICIENCY CHANGE AND ENERGY INPUT. AN INTERNATIONAL FRONTIER ANALYSIS

♣Luis R. Murillo-Zamorano[a,b]

[a] Department of Economics and Related Studies, University of York, Heslington, YO105DD, York, UK
E-mail address: lrmz101@york.ac.uk
[b] Department of Economics, University of Extremadura, Avda. de Elvas s/n , 06071 Badajoz, Spain
E-mail address: lmurillo@unex.es

April 2003

Abstract

The main objective of this paper is to clarify the controversial role of energy in productivity growth. This is done by reconciling conventional approaches to the measurement of aggregated productivity growth with the microeconomic foundations provided by the energy economics and frontier productivity measurement literature. The use of Malmquist productivity indices allows us to broaden previous research by decomposing productivity growth into technological progress and technical efficiency change as well as analysing the relationship between energy and both sources of productivity change. By doing so, our findings are that energy indeed matters and that the consideration of technical efficiency contributes to a better understanding of both the temporal evolution and cross-country variability of aggregated productivity growth.

Keywords: Energy input, Total factor productivity growth, Technical efficiency change, Malmquist productivity growth indices.

JEL classification: Q43; O30; O47

♣ The author is most grateful to B. Beaudreau, H. Dixon, K. Mumford, S. Perelman, and J. Vega for their valuable comments, and to the Junta de Extremadura for financial support.

1. Introduction

The contribution of energy to the productivity of industrialized countries is a controversial topic in economic theory**.** The initial works of Schurr (1983), Rosenberg (1983), and Jorgenson (1983, 1984) left no room for doubt about the importance of the energy factor in productivity. They analysed the industrial sectors of the United States, and concluded that energy plays a fundamental role in the temporal evolution of productivity. Later work, however, such as that of Denison (1985) and Gullickson and Harper (1987) called those claims into question. These authors based their work on demonstrating that energy has little weight in output growth, so that its oscillations have hardly any influence on total factor productivity (TFP) growth. They showed that the energy crises of 1973 and 1979 had only slight importance in the productivity declines of the OECD countries during the 1980s.

Other authors, such as Field and Grebenstein (1980), Berndt, Morrison and Watkins (1981), Berndt and Watkins (1981), Pindyck and Rotemberg (1983), Kintis and Panas (1989), and more recently Watkins and Berndt (1991), Hisnanick and Kymm (1992), Gowdy (1992), Hisnanick and Kyer (1995), and Beaudreau (1995) have also addressed the relationship of energy with the structure of production and the subsequent role of energy in productivity growth. The approaches used include dynamic models, dual-KLE technology specifications, energy input disaggregation, and alternative productive factor computations. Despite all this research effort, there seems to be no unanimity of criteria yet to explain the relationship between productivity growth and energy input.

In an attempt to achieve a better understanding of this controversial issue, unlike previous literature which has mainly focused on just the measurement of economic performance at the manufacturing level, this paper extends the research to an international pooled cross-section framework where most industrialized OECD countries are observed at an aggregated level. In this macroeconomic context, energy input has regularly been neglected as a relevant factor within the structure of production[1]. Moreover, productivity growth has also tended to be identified with

[1] Apostolakis (1984, 1987) and Vega-Cervera and García-Hierro (2000) constitute exceptions to this general rule.

technological progress ignoring the importance of economic efficiency variations as a further source of productivity change. In our view, none of these approaches are in accord with the microeconomic foundations provided by the energy economics and frontier productivity measurement literature.

Thus, the main purpose of this paper is to reconcile conventional approaches to the analysis of aggregated productivity growth with the underlying economic theory and so be able to shed some light on the controversial role played by energy input. This is done first by decomposing productivity growth into technological progress and economic efficiency change, and second by modeling energy consumption as a relevant input in the technological setting of the industrialized countries. To the best of our knowledge, this is the first time that the above microeconomic underpinnings have been satisfactorily combined within a macroeconomic framework.

In doing so, the decomposition of productivity growth helps one to understand the traditionally ambiguous and as yet insufficiently well-interpreted effect of energy on productivity growth. Thus, our results suggest a clear relationship between energy consumption and productivity growth. Technical efficiency seems to explain a significant part of the variability of productivity over time and across countries. And higher energy prices due to oil shocks appear also to be important in the explanation of the productivity growth slowdown during the 1973 and 1979 energy crises.

The rest of the paper proceeds as follows. The theory underlying our approach is presented in Section 2 where the techniques used to calculate the productivity growth indices are also introduced. Section 3 contains a discussion of the data set and main empirical results. Finally, Section 4 presents the conclusions.

2. The measurement of productivity growth

The earliest approaches to the measurement of productivity[2] were based on partial indicators[3], where an index of aggregate output is divided by the observed quantity of a single input, generally labour. These partial measures provide a misleading

[2] See Nadiri (1970) for a survey of productivity theory.
[3] This approach was used in Denison (1962, 1967, 1974) and Kendrick (1961, 1973).

indicator of overall productivity. A more accurate approach to the measurement of productivity is based on total factor productivity measures[4] which involve all outputs and factors of production. These are the measures we shall use in this investigation.

The economic literature provides us with an ample set of methods to determine the TFP growth of a sample of both micro- and macro-economic units. These methods can be grouped into two main types: frontier and non-frontier techniques. The conventional approach to productivity measurement by means of non-frontier models (and within this group the growth accounting[5] and the index number[6] approaches) assumes that all individuals are efficient. Hence, these methods tend to identify TFP growth with technological progress. Moreover, since Solow´s (1957) seminal contribution, this identification has also been exported to the analysis of economic growth sources by means of both the above neoclassical growth models and more recent endogenous growth theories[7]. However, as is pointed out by Nishimizu and Page (1982), such a type of analysis neglects another important source of TFP growth: economic efficiency change. While technological progress, through the adoption of technical innovations, pushes the frontier of potential production upward, efficiency change reflects the capacity of productive units to improve production with a set of given inputs and the available technology.

The starting point to measure both technical efficiency and productivity will be to estimate a production frontier that allows for the measurement of technological progress. Most of the papers related to this topic have based their analyses on either parametric or non-parametric methods. The choice of estimation method is a major issue of debate, with some researchers preferring the parametric approach[8] and others the non-parametric.[9] The main disadvantage of non-parametric approaches is their deterministic nature that precludes the distinction between technical inefficiency and statistical noise effects. On the other hand, parametric frontier functions require the

---

[4] See Cowing and Stevenson (1981) and Coelli, Rao and Battese (1998), Hulten (2000) and OECD (2001) for excellent surveys of these measures.
[5] Solow (1957), Denison (1972).
[6] Baumol (1986), Dollar and Wolff (1994), Bernard and Jones (1996a).
[7] Romer (1986, 1989), Lucas (1988).
[8] Berger (1993).
[9] Seiford and Thrall (1990).

definition of a specific functional form for the technology and for the inefficiency error term which usually causes both specification and estimation problems[10].

In this study, the inherent characteristics of the sample of observations and the greater flexibility that characterizes non-parametric techniques, which require neither a functional form for the frontier nor an assumption about the distribution of the error term, led us to adopt the latter approach. Namely, we use the productivity indices proposed by Färe, Grosskopf, Lindgren and Roos (1994). These indices calculate productivity change as the geometric mean of two Malmquist productivity indices[11] and allow changes in productivity to be decomposed into changes in efficiency and technical progress.

To define a Malmquist index of productivity change we must explore the concept of an output distance function[12]. Following Shepard (1970) and Caves, Christensen and Diewert (1982), this is defined at t as

$$D_0^t(x^t, y^t) = \inf\left\{\theta : (x^t, y^t / \theta) \in S^t\right\} \qquad (2.1)$$

where S^t represents the production technology for each time period $t=1,..T$. This technological set models the transformation of a vector of inputs $x^t = (x^t_1,...,x^t_M) \in R^+_M$ into a vector of outputs $y^t = (y^t_1,...,y^t_N) \in R^+_N$, both corresponding to period t:

$$S^t = \left\{(x^t, y^t) : x^t \text{ can produce } y^t \right\} \qquad (2.2)$$

The function $D_o^t(.)$ is defined as the reciprocal of the maximum expansion to which it is necessary to subject the vector of outputs of period t (y^t) given the level of inputs (x^t) so that the observation stands at the frontier of period t. This function fully characterizes the technology in such a way that $D^t_0(x^t, y^t) \leq 1$ if and only if $(x^t, y^t) \in S^t$. Moreover, $D^t_0(x^t, y^t) = 1$ if and only if the observation is technically efficient according to the terminology used in Farrell (1957).

[10] See Murillo-Zamorano and Vega-Cervera (2001) for a comparative analysis of both parametric and non-parametric groups of techniques.
[11] Malmquist indices were first so-named by Caves, Christensen and Diewert (1982) in their work based on Malmquist (1953) who had previously presented input quantity indices as ratios of distance functions.
[12] The input distance function is defined similarly. See Deaton (1979) for some applications.

In order to implement the Malmquist productivity index, it is also necessary to define the above distance function with respect to two time periods such as $D^t_0\,(x^{t+1}, y^{t+1})$ and $D^{t+1}_0\,(x^t, y^t)$. In both these mixed-period cases, the value of the distance function may exceed unity. This happens when the unit being analysed in one period is not feasible in the other. In particular, if $D^t_0\,(x^{t+1}, y^{t+1})>1$ there has been technical progress, while if $D^{t+1}_0\,(x^t, y^t)>1$ there has been technical regression.

On the basis of the above output distance functions defined for a variable returns to scale reference technology[13], Caves, Christensen and Diewert (1982) defined their output oriented Malmquist productivity indices for period t and $t+1$ respectively as

$$M_O^t(x^t, y^t, x^{t+1}, y^{t+1}) = \frac{D_O^t(x^{t+1}, y^{t+1})}{D_O^t(x^t, y^t)} \tag{2.3}$$

$$M_O^{t+1}(x^t, y^t, x^{t+1}, y^{t+1}) = \frac{D_O^{t+1}(x^{t+1}, y^{t+1})}{D_O^{t+1}(x^t, y^t)} \tag{2.4}$$

Each of the above output based productivity indices will generally produce a different productivity indicator unless the reference technology is Hicks output neutral[14]. To avoid the need to either impose this constraint or subjectively decide for one of the technologies, some authors define an additional productivity index as the geometric mean of these two indices[15]:

$$M_O(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\left(\frac{D_O^t(x^{t+1}, y^{t+1})}{D_O^t(x^t, y^t)}\right)\left(\frac{D_O^{t+1}(x^{t+1}, y^{t+1})}{D_O^{t+1}(x^t, y^t)}\right)\right]^{1/2} \tag{2.5}$$

where $M_O\,(.)$ is the composed geometric mean of two Malmquist productivity indices: the first evaluated with respect to technology at time t, and the second with respect to technology at time $t+1$[16].

---

[13] Hereafter, all functions refer to variable returns to scale unless subscripted with a "*c*" to indicate constant returns to scale.
[14] This issue is noted and analysed in Färe, Grosskopf and Roos (1998).
[15] A first example of this strategy can be found in Fisher (1922).
[16] Caves, Christensen and Diewert (1982) showed that the geometric mean of two input/output Malmquist quantity indices was equal to a Tornqvist (1936) input/output quantity index. Moreover, assuming a

The idea of using the geometric mean of two Malmquist productivity indices is also exploited in the key work of Färe, Grosskopf, Lindgren and Roos (1994). Unlike the Caves, Christensen and Diewert (1982) index where productive units are assumed to be fully allocatively and technically efficient, the *FGLR Malmquist productivity index* allows for the presence of inefficiency. This enables a further decomposition of the productivity growth into technological progress and efficiency change[17]. For the output-oriented case[18], this decomposition is recovered from the expression

$$M_{OC}(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D_{OC}^{t+1}(x^{t+1}, y^{t+1})}{D_{OC}^{t}(x^t, y^t)} \left[\left(\frac{D_{OC}^{t}(x^{t+1}, y^{t+1})}{D_{OC}^{t+1}(x^{t+1}, y^{t+1})} \right) \left(\frac{D_{OC}^{t}(x^t, y^t)}{D_{OC}^{t+1}(x^t, y^t)} \right) \right]^{1/2} \tag{2.6}$$

where the first ratio represents the change in relative efficiency[19] between periods *t* and *t+1*, and the geometric mean of the two ratios in the brackets measures the change or movement of technology between periods *t* and *t+1*. A $M_{OC}(.)$ greater than one implies that productivity has risen between period *t* and *t+1*. This rise can be explained on the basis of a technical efficiency improvement and/or technical progress.[20]

---

translog technology with identical second-order terms and profit maximization, Equation 2.5 can be expressed as a Tornqvist productivity index plus a scale factor to account for the presence of variable returns to scale. A systematic analysis of the relationships between Tornqvist and Malmquist quantity, price, and productivity indices can be found in Coelli, Rao and Battese (1998).

[17] Although Caves, Christensen and Diewert (1982) did not decompose their productivity indices, it is straightforward to do so. Thus, for the *t* period Malmquist productivity index, $M^t_O(x^t,y^t,x^{t+1},y^{t+1})= D^t_O(x^{t+1},y^{t+1})/D^t_O(x^t,y^t)= [D^t_O(x^{t+1},y^{t+1})/D^{t+1}_O(x^{t+1},y^{t+1})][D^{t+1}_O(x^{t+1},y^{t+1})/D^t_O(x^t,y^t)]$ where the first factor in brackets measures technical change using period *t+1* data and the second is the technical change component calculated under a variable return to scale reference technology.

[18] Under some productive frameworks where output is given, the idea of measuring efficiency and productivity change on the grounds of maximum proportional reductions in all inputs given an available technology by means of input distance functions rather than output ones may provide important insights. This reasoning led to the literature on the computation of *Malmquist input-based measures of productivity change* such as those utilized in Färe, Grosskopf, Yaisawarng, Li and Wang (1990), Berg, Forsund and Jansen (1992), Färe, Grosskopf, Lindgren and Roos (1992), and more recently in Yaisawarng and Klein (1994) and Fukuyama and Weber (1999).

[19] This ratio, corresponding to the ratio of the Farrell (1957) technical efficiency in period t+1 to the Farrell's technical efficiency in period *t*, will be greater than one if there is an increase in efficiency.

[20] If there is no change in efficiency between *t* and *t+1*, the changes in the *FGLR Malmquist productivity index* will be explained only by the movement of the frontier. If the second term of M_{OC} is 1 (no technical change), the changes in productivity will be explained only by the changes in efficiency of units over time periods. In other cases, the productivity changes will be a mixture of changes in efficiency and technical progress/regression.

The above decomposition can be interpreted in terms of Figure 1 for a single output/single input constant returns to scale technology where a technological advance ($S^t \subset S^{t+1}$) occurs from t to $t+1$.

<<Figure 1>>

In Figure 1, the productive unit is operating at (x^t, y^t) and (x^{t+1}, y^{t+1}) input/output bundles at t and $t+1$ respectively. These observations lie below the technologically efficient frontiers (S^t, S^{t+1}) at both the t and $t+1$ time-periods, and consequently correspond to non-technically efficient combinations. In terms of distances along the y-axis, the decomposition of (2.6) is equivalent to the following expressions for technical efficiency change and technical change,

$$\text{Technical efficiency change} = \frac{y^{t+1} \big/ y^{t+1,t+1}}{y^t \big/ y^{t,t}} \tag{2.7}$$

$$\text{Technical change} = \frac{y^{t+1} \big/ y^{t+1,t}}{y^{t+1} \big/ y^{t+1,t+1}} \times \frac{y^t \big/ y^{t,t}}{y^t \big/ y^{t,t+1}} \tag{2.8}$$

where $y^{t,t}$, $y^{t,t+1}$, $y^{t+1,t}$, $y^{t+1,t+1}$ represent the maximum attainable level of output for x^t and x^{t+1} levels of input for each of the technological sets (S^t and S^{t+1}) considered.

Färe, Grosskopf, Lindgren and Roos (1994) were also the first to note that, as the output distance function is the reciprocal of Farrell's output-oriented technical efficiency measure, and given suitable panel data, the distance functions involved in (2.6) can be calculated by using linear programming techniques of the Data Envelopment Analysis (DEA) type[21]. Hence, for any cross-section unit i, $D^t_{OC}(x^t, y^t)$ is solved as

[21] Data Envelopment Analysis is first introduced in Charnes, Cooper and Rhodes (1978). A more detailed analysis of alternative formulations can be found in Ali and Seiford (1993) and Coelli, Rao and Battese (1998).

$$\left[D_O^t(x_i^t, y_i^t)\right]^{-1} = \max_{\lambda} \Phi_i^{t,t}$$

s.t.

$$\begin{aligned}
&\sum_{k=1}^{K} \lambda_k^t y_{sk}^t \geq \Phi_i^{t,t} y_{si}^t \qquad && s = 1...S \qquad (2.9)\\
&\sum_{k=1}^{K} \lambda_k^t x_{mk}^t \leq x_{mi}^t && m = 1...M\\
&\lambda_k^t \geq 0 && k,i = 1...K
\end{aligned}$$

where K represents the number of cross section units for each time period within the panel data, S and M indicate outputs and inputs respectively, and λ_k^t measures the weight of each cross section unit within the peer group to which any particular observation is compared in order to determine the distance to the efficient frontier. The calculation of $D_O^{t+1}(x_i^{t+1}, y_i^{t+1})$ is identical to $D_O^t(x_i^t, y_i^t)$ but substituting *t+1* for *t*. With respect to the distance functions involving mixed periods of time, $D_O^t(x^{t+1}, y^{t+1})$ for unit *i* is computed as

$$\left[D_O^t(x_i^{t+1}, y_i^{t+1})\right]^{-1} = \max_{\lambda} \Phi_i^{t,t+1}$$

s.t.

$$\begin{aligned}
&\sum_{k=1}^{K} \lambda_k^t y_{sk}^t \geq \Phi_i^{t,t+1} y_{si}^{t+1} \qquad && s = 1...S \qquad (2.10)\\
&\sum_{k=1}^{K} \lambda_k^t x_{mk}^t \leq x_{mi}^{t+1} && m = 1...M\\
&\lambda_k^t \geq 0 && k,i = 1...K
\end{aligned}$$

and $D_O^t(x^{t+1}, y^{t+1})$ is calculated as above but transposing the *t* and *t+1* superscripts.

In addition to its wide use[22], the Malmquist productivity index so far described present a number of major advantages over the conventional approaches to the measurement of productivity within a non-frontier framework, namely the Tornqvist

[22] Malmquist-type productivity indices have been applied to a wide range of both microeconomic and macroeconomic studies. A recent survey of this empirical literature covering studies of the banking, electric utilities, transportation, insurance, agriculture, and public sectors, as well as national and international comparison studies can be found in Färe, Grosskopf and Roos (1998).

(1936) and Fisher (1922) index numbers. Thus, as was noted above, the Malmquist productivity index permit TFP growth to be decomposed into technological change and technical efficiency change. It does not require price information to be implemented nor any behavioural assumption such as cost minimization, revenue maximization, or profit maximization to be made. This makes it preferable in situations where prices are distorted or missing, and in those other cases in which producers' objectives are different, unknown, or simply unfeasible. Moreover, under certain conditions it can be linked to the conventional indices as is detailed in Caves, Christensen and Diewert (1982), Färe and Grosskopf (1992), and Balk (1993).

3. Data and results

The countries considered in our study are the European Union nations except Germany[23], plus Australia, Canada, Japan, and USA. The aggregate output of each country is measured by its Gross Domestic Product (GDP). The total capital stock is calculated from the non-residential capital per worker. Both capital stock and GDP variables are expressed in 1985 international prices as retrieved from the Penn World Tables (Mark 5.6)[24]. The labour variable, also retrieved from the Penn World Table, and computed from real GDP per worker, represents total employment. Finally, the energy input, taken from the Energy Balances of the OECD countries, is obtained by reducing the total consumption of primary energy by the gross consumption of private households[25].

The empirical estimation process in this section will be developed in two stages. The first involves the decomposition of productivity growth on the basis of considering GDP as output, and capital and labour as unique relevant productive inputs. In the second, we shall first check for the statistical relevance of energy input, and then recalculate the productivity growth indices taking the energy input into account together with the classical productive factors of capital and labour. Finally, a graphical and comparative analysis of the productivity scores reached with and without energy will also be discussed.

[23] The reunification process precludes the availability of data on the energy variable.
[24] This is an updated version of Summers and Heston (1991).
[25] In doing so we avoid the endogeneity of energy input with GDP given that, as is known, household energy consumption is already accounted for in the GDP.

3.1. Classical factors and productivity growth

We initially calculate[26] a set of Malmquist productivity indices taking GDP as output and capital and labour as the only relevant inputs. As Färe, Grosskopf, Lindgren and Roos (1994) note, since this is an index based on discrete time, each country will have an index for every pair of years. This entails calculating the component distance functions using linear programming methods such as those described above. Instead of presenting the disaggregated results for each country and year, we next collect in Table 1 the average annual rates[27] for TFP growth (Tfpch), technological progress (Techch), and efficiency change (Effch).

<< Table 1 >>

The results show there to be a major variability of TFP growth rates across countries. Thus, Finland attains the highest productivity growth rate (1.8%), followed by Luxembourg, and Belgium. A greater number of countries experienced on average productivity declines, with Spain (-1.7%) and Japan (-1.2%) having lowest average TFP growth rates.

As an aid to the further analysis of the productivity levels, Figures 2-4 present the cumulative evolution of the Malmquist productivity index and its breakdown into technical progress and efficiency change accumulated components for the EU, Japan, USA, Australia, and Canada[28].

<< Figure 2 >>

<< Figure 3 >>

<< Figure 4 >>

According to Figure 2, Australia and Canada present a clear rise in their productivity levels over the time period considered. Also, the USA's accumulated

[26] Linear programming problems required to implement the Malmquist productivity indices can be solved using any of a variety of computer programs. We use DEAP Version 2.1. A detailed description of the computer program is provided in Coelli (1996a).

[27] These rates are calculated as geometric means due to the multiplicative nature of the Malmquist index. Disaggregated results are available on request.

[28] These accumulated scores are calculated as the sequential multiplicative sums of the annual indices.

productivity levels are clearly above the European and especially the Japanese levels. Also, while Europe and the USA present a more or less stable trend around the steady state, Japan shows a major loss of productivity.

With respect to the accumulated levels of technical progress, one sees from Figure 3 that the differences between countries are less pronounced and the behavioural trend is far more homogeneous. It would seem therefore that the main determinant of the differentiated behaviour of the productivity is to be sought in the temporal evolution of the accumulated efficiency, as can be seen in Figure 4. This graphical analysis hence shows the importance of decomposing TFP growth into technological progress and technical efficiency change in order to better understand productivity growth.

Finally, looking more closely at the aforementioned figures, one sees how higher energy prices during the 1973 and 1979 oil price shocks are associated with a decline in both the technological progress and productivity growth accumulated levels. Some authors, such as Denison (1985) and Gullickson and Harper (1987), have concluded that energy prices have no impact on the growth of output at aggregate level since energy itself is only a small proportion of aggregate output. Our results point to the contrary. In line with Jorgenson (1984, 1988b) energy crises seem to be related with the decline in technological progress and productivity growth of industrialized countries and hence with their economic growth slowdown. As in Jorgenson (1988a), our results seem to support the idea that energy crises could revert production methods to periods of technological development that existed before the oil price shocks. In this post-crisis technological set, the energy price trends could result in the substitution of capital, labor, and material inputs for energy, thus reducing the energy intensity of production. Different cross-country success in handling these inputs might be responsible for the heterogeneous path followed for the technical efficiency accumulated levels plotted in Figure 4.

3.2. Energy factor and productivity growth

As Norsworthy and Malmquist (1983) note, the aforementioned energy crises have highlighted the importance of including energy input in the analysis of economic and productivity growth. In the literature, the typical form of investigating the issue of whether or not a production factor such as energy is a relevant input is based on two econometric production models, in which the more general model includes this factor, while the second does not. The more general model is then tested against the restricted model, which is nested within the more general model.

An immense variety of model specifications and estimation techniques are available in the specialized literature for the econometric analysis of frontier functions[29] such as those needed to address this issue. In this study, following Battese and Coelli's (1992) approach[30], two alternative specifications –Model 1 and Model 2– are implemented to check for the statistical significance of the energy input. Model 1 represents a Cobb-Douglas production frontier function where the technical inefficiency effects are assumed to be time-variant and to have a truncated-normal distribution. Model 2 defines a translog production function with technical inefficiency effects varying over time and also with a truncated-normal distribution.

The values of the log-likelihood functions for the general and restricted version of each of these models are listed in Table 2. The generalized likelihood-ratio statistic for testing the null hypothesis that the energy factor is not statistically significant is also given. This value compared with the upper one percent for the chi-squared distribution critical value indicates the rejection of the null hypothesis for any of the alternative specification tested.

<< Table 2 >>

Moreover, applying a non-parametric test based on the inefficiency scores reported by DEA-like linear programming problems, namely the *Banker test*, we also find energy consumption to be a statistically significant productive input to be considered in the definition of the frontier technological set. The Banker test, developed in Banker (1996), checks for the significance of a set of additional variables introduced into a DEA model on the basis of their asymptotic properties. If the inefficiency is distributed as half-normal, the Banker test is distributed as $F_{n,n}$ with n indicating the

[29] The reader is referred to Murillo-Zamorano (2003) for a comprehensive and updated analysis of both parametric and non-parametric techniques for the measurement of economic efficiency.
[30] See the Appendix for details on this section.

number of observations. In our case, under the null hypothesis that energy does not influence the production correspondence between the output and the inputs, we get an F^* critical value of 2.6350, which implies the rejection of the null hypothesis at a 99% confidence level.

Given this set of parametric and non-parametric statistical tests, it seems to be both advisable and convenient to consider energy consumption as a relevant productive input. If we did not, every change in energy consumption levels would be absorbed by the other inputs, and therefore capital and labour would seem to be artificially more productive[31]. Moreover, not including the energy input would lead to a bias in the levels and temporal evolution of the productivity attained by the countries of the study.

The decomposition of TFP growth including energy input as an additional productive input is also given in Table 1. The new scores show a generalized increase in the rates of productivity growth, as can be seen by comparing the average productivity growth rates with (+0.6%) and without (-0.001%) energy.

By countries, Belgium, Canada, Ireland, France, and USA have greater positive productivity growth rates, while Portugal, Spain, and the UK have smaller negative growth rates when the energy input is introduced. Austria, Denmark, Italy, Japan, Netherlands, and Sweden present changes that are important qualitatively as well as quantitatively, moving from negative to positive productivity growth rates. Australia, Finland, and Luxembourg maintain the same rates. Only Greece shows a recession in its productivity. In sum, most of the countries (fourteen out of eighteen) have increased productivity growth rates.

An international comparison of the incidence of energy in productivity growth sources is shown in Figures 5-7. In these figures, the vertical axis is the performance

[31] On the basis of a satisfactory statistical significance, other productive factors such as public capital, human capital, or materials could also be considered as further inputs within the structure of the production. The incidence of human and public capital in productivity growth has been explored in Grosskopf and Self (2001) and Petraglia (2003), respectively. As for materials, their consideration within the specification of the productive technology has been an issue of debate, with some researchers using KLEM models (e.g. Berndt and Wood, 1975, and Morrison and Berndt, 1981) and others KLE models (e.g. Iqbal, 1986 and Apostolakis, 1987). In our case, the lack of consistent information for international panel data at an aggregated level such as that employed in this paper simply precludes their implementation.

including energy, and the horizontal axis the performance without energy. Observations above the 45º bisectrix represent performance improvements in terms of productivity growth (Figure 5), technological change (Figure 6), and efficiency change (Figure 7). As can be seen, this expansion is clearly homogeneous in terms of both productivity and technological progress, while there is a greater variability in terms of rates of technical efficiency change.

<< Figure 5 >>

<< Figure 6 >>

<< Figure 7 >>

Lastly, moving from an analysis in terms of growth rates to one in terms of cumulative levels, the improvement in the productivity growth rate as a consequence of the introduction of the energy input may also be deduced from the graphical comparison of Figures 8-10 with Figures 2-4. In particular, if one again focuses on the 1973 and 1979 energy crises, new comments suggest themselves. As before, the 1973 oil price shock seems to generate a decline in technological progress of the industrialized countries, which could suggest the existence of an energy-using productive technology. As Jorgenson (1988b) points out, if technological progress is energy using, then the rate of technical change declines when the price of energy increases. However, Figure 9 shows that this decline in technological progress rates is not so homogeneous after the 1979 energy crisis. In line with Jorgenson (1998b), it would seem that some countries such as Japan and Australia have adopted energy-saving productive technologies which would have precluded the corresponding reduction in technological progress associated with an energy-using technical change. On the other hand, others such as Canada and USA seem to continue to employ energy-using technologies. These cross-country differences are also observed in the productivity accumulated scores of Figure 8, and the technical efficiency accumulated levels of Figure 10.

<< Figure 8 >>

<< Figure 9 >>

<< Figure 10 >>

In sum, both efficiency variation and technological change help to explain the evolution of productivity over time. Some of the more relevant results of a closer study of the statistical significance of the relationships between the above sources of productivity growth and energy consumption are presented in Table 3. In terms of simple statistical correlation, there seems to be a clear relationship between energy and productivity as well as between energy and both technological progress and productive efficiency. Therefore, the failure to consider the technical efficiency component and the identification of the total productivity growth of the factors with technological progress may lead to the appearance of biased, and even simply incorrect, results. The inclusion of this component, however, seems to clarify the variability of productivity growth across countries as well as the different role played by energy in the evolution of that growth.

<< Table 3 >>

4. Conclusions

The role played by energy in productivity growth is a controversial topic. While part of the empirical evidence suggests that the energy input plays a fundamental role in productivity change, other studies point to the contrary. Nevertheless, both these streams of research have focused mostly on the analysis of the manufacturing sector only. Our results are clearly in support of the former group, extending their findings to a fully aggregated framework, and providing strong evidence for an active role of energy in the productivity growth of industrialized countries.

In this respect, the main methodological contribution of the present work has been to reconcile conventional approaches to the measurement of aggregated productivity growth with the underlying microeconomic theory developed in the energy economics and frontier productivity measurement literature. In doing so, we find that technical efficiency seems to explain a significant part of the variability of productivity over time and across countries. Therefore, the traditional identification of productivity growth with technological progress made in much of the previous literature seems not to be appropriate. Indeed, neglecting technical efficiency could lead to biased, and simply incorrect, results.

The decomposition of productivity growth into technological progress and technical efficiency change also seems to shed light on the critical role of the increase in energy prices after the 1973 and 1979 oil crises. Our results show that the higher energy prices during those crises are also important in explaining the temporal evolution and cross-country variability of productivity growth rates. This might also improve the assessment of the economic growth slowdown during those periods and move frontier productivity measurement and the modeling of energy as a relevant input in the technological setting of the industrialized countries into the economic growth literature where they certainly belong.

In line with the above, considerable theoretical and empirical work still remains to be done. Thus, the drastic changes in relative prices of capital, labour, and energy, especially after energy crises, make it advisable to implement dual parametric frontier approaches to the measurement of productivity growth in which input prices could be taken into account. This would also provide new insights into the traditional energy-capital complementarity/substitutability dichotomy and thus permit a more stylized and suitable framework for the discussion of alternative economic policies. Greater rationality would also be introduced by using dynamic models where some inputs may be modeled as fixed or quasi-fixed inputs. Finally, a breakdown of labour into production (blue-collar) and non-production (white-collar) workers, as well as distinguishing between physical and worker capital or energy disaggregated into electrical and non-electrical components is also a task for future research. In any case, although much work remains to be done, we believe that the preliminary step taken here provides important insights not only into how to revitalize the role played by energy in the industrialized countries' sources of productivity growth but also into the way of approaching its measurement and analysis.

References

Aigner, D.J., C.A.K. Lovell and P.J. Schmidt, 1977, Formulation and estimation of stochastic frontier production function models, Journal of Econometrics 6, 21-37.

Ali, A.I. and L.M. Seiford, 1993, The mathematical programming approach to efficiency analysis, in: Harold O. Fried, C.A.K. Lovell and S.S. Schmidt (Eds.), The Measurement of Productive Efficiency: Techniques and Applications, (Oxford :Oxford University Press), 121-159.

Apostolakis, B.E., 1984, Energy demand in an aggregate cost specification, Economia di Energia 24, 85-95.

Apostolakis, B.E., 1987, The role of energy in production functions for southern European economies, Energy 12(7), 531-541.

Balk, B.M., 1993, Malmquist productivity indexes and Fisher ideal indexes: comment, Economic Journal, 103 (415), 680-682.

Balk, B.M., 1998, Input price, quantity, and productivity indexes for a revenue-constrained firm, in: R. Färe, S. Grosskopf and R.R. Russell (Eds.) Index Numbers: Essays in Honour of Sten Malmquist, (Kluwer Academic Publishers: Boston), 91-126.

Banker, R.D., 1996, Hypothesis tests using data envelopment analysis, The Journal of Productivity Analysis 7, 139-159.

Battese, G.E. and T.J. Coelli, 1988, Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data. Journal of Econometrics 38, 387-399.

Battese, G.E. and T.J. Coelli, 1992, Frontier production functions, technical efficiency and panel data: with application to Paddy farmers in India, Journal of Productivity Analysis 3(1-2), 153-169.

Battese, G.E., T.J. Coelli, and T. Colby, 1989, Estimation of frontier production functions and the efficiencies of Indian farms using panel data from ICRISTAT's village level studies. Journal of Quantitative Economics 5 (2), 327-348.

Battese G. and G. Corra, 1977, Estimation of a production frontier model with application to the pastoral zone of Easter Australia, Australian Journal of Agricultural Economics 21(3), 167-179.

Baumol, W., 1986, Productivity growth, convergence, and welfare: what the long run data show, American Economic Review 76, 72-85.

Beaudreau, B.C., 1995, The impact of electric power on productivity, Energy Economics 17, 231-236.

Berg, S., F.R. Forsund and E.S. Jansen, 1992, Malmquist indices of productivity growth during the deregulation of Norwegian banking, 1980-89, Scandinavian Journal of Economics, 94 (Supplement), 211-228

Berger, A.N., 1993, Distribution-free estimates of efficiency in the U.S. banking industry and tests of the standard distributional assumptions, Journal of Productivity Analysis 4, 261-292.

Bernard, A.B. and C.I. Jones, 1996a, Technology and convergence, The Economic Journal 106, 1037-1044.

Bernard, A.B. and C.I. Jones, 1996b, Comparing apples to oranges: productivity convergence and measurement across industries and countries, American Economic Review 86, 1216-1238.

Berndt, E.R., C.J. Morrison and G.C. Watkins, 1981, Dynamic models of energy demand: an assessment and comparison, in: Berndt, E.R. and B.C. Field (Eds.),

Modeling and Measuring Natural Resource Substitution, (Cambridge MIT Press), 259-289.
Berndt, E.R. and G.C. Watkins, 1981, Energy prices and productivity trends in the Canadian manufacturing sector, 1957-1976: some explanatory results, Ottawa, Economic Council of Canada.
Berndt, E.R. and D.O. Wood, 1975, Techonolgy, prices, and the derived demand for energy, Review of Economics and Statistics 57, 376-384.
Caves, D.W., L.R. Christensen and W.E. Diewert, 1982, The economic theory of index numbers and the measurement of input, output, and productivity, Econometrica 50(6), 1393-1414.
Charnes, A., W.W. Cooper and E. Rhodes, 1978, Measuring the efficiency of decision-making units, European Journal of Operational Research, 2, 429-444.
Coelli, T., 1996a, A guide to FRONTIER version 4.1: a computer program for stochastic frontier production and cost function estimation, CEPA Working Paper 96/07.
Coelli, T., 1996b, A guide to DEAP version 2.1: a data envelopment analysis (computer) program, CEPA Working Paper 96/08.
Coelli, T., D.S.P. Rao and G.E. Battese, 1998, An introduction to efficiency and productivity analysis (Kluwer Academic Publishers, Boston).
Cornwell, C., P. Schmidt and R.C. Sickles, 1990, Production frontiers with cross-sectional and time-series variations in efficiency levels. Journal of Econometrics 46(1/2), 185-200.
Costello, D.M., 1993, A cross-country, cross-industry comparison of productivity growth, Journal of Political Economy 101, 207-222.
Cowing, T.G. and R.E. Stevenson, 1981, Productivity measurement in regulated industries (Academic Press, Inc., New York).
Deaton, A., 1979, The distance function and consumer behaviour with applications to index numbers and optimal taxation, Review of Economic Studies 46, 391-405.
Denison, E.F., 1962, The sources of economic growth in the U.S. and the alternatives before us (Committee for Economic Development, Supple. Paper No.13, New York).
Denison, E.F., 1967, Why growth rates differ: post-war experience in nine Western countries (The Brookings Institution, Washington, D.C.).
Denison, E.F., 1972, Classification of sources of growth, Review of Income and Wealth 18, 1-25.
Denison, E.F., 1974, Accounting for United States economic growth, 1929 to 1969 (The Brookings Institution, Washington, D.C.).
Denison, E.F., 1985, Trends in American economic growth, 1929-1982 (The Brookings Institution, Washington D.C.).
Deprins, D., L. Simar and H. Tulkens, 1984, Measuring labour-efficiency in post offices, in: J. Marchand, G. Pestieau and H. Tulkens, eds., The Performance of Public Enterprises. Concept and Measurement (Nort Holland, Amsterdam).
Dollar, D. and E.N. Wolff, 1994, Capital intensity and TFP convergence by industry in manufacturing, 1963-1985, in: W.J. Baumol, R.R. Nelson and E.N. Wolf, eds., Convergence of Productivity, Cross-National Studies and Historical Evidence (Oxford University Press, Oxford).
Färe, R., Grifell-Tatjé, S. Grosskopf and C.A.K. Lovell, 1997, Based technical change and the Malmquist productivity index, Scandinavian Journal of Economics, 99, 119-127.
Färe, R. and S. Grosskpof, 1992, Malmquist indexes and Fisher ideal indexes, Economic Journal, 102 (410), 158-160.

Färe, R. and S. Grosskopf, 1994, Cost and Revenue Constrained Production, Billant University Lecture Series Volume 4, Springer-Verlag, New York.
Färe, R. and S. Grosskopf, 1996, Intertemporal production frontiers: with dynamic DEA (Kluwer Academic Publishers, Boston).
Färe, R., S. Grosskopf, B. Lindgren and P. Roos, 1992, Productivity changes in Swedish pharmacies 1980-1989: A nonparametric Malmquist approach, Journal of Productivity Analysis, 3, 85-101.
Färe, R., S. Grosskpof, B. Lindgren and P. Roos, 1994, Productivity developments in Swedish hospitals: A Malmquist output index approach, in: A. Charnes, W.W. Cooper, A.Y. Lewin and L.M. Seiford, eds., Data Envelopment Analysis: Theory, Methodology and Applications (Kluwer Academic Publishers, Boston).
Färe, R., S. Grosskopf and C.A.K. Lovell, 1994, Production Frontiers (Cambridge University Press, Cambridge).
Färe, R., S. Grosskpof, M. Norris and Z. Zhang, 1994, Productivity growth, technical progress, and efficiency changes in industrialised countries, American Economic Review 84, 66-83.
Färe, R., S. Grosskopf and P. Roos, 1998, Malmquist productivity indexes: A survey of theory and practice, in: R. Färe, S. Grosskopf and R.R. Russell eds., Index Numbers: Essays in Honour of Sten Malmquist (Kluwer Academic Publishers, Boston): 127-190.
Färe, R., S. Grosskopf, S. Yaisawarng, S.-K. Li and Z. Wang, 1990, Productivity growth in Illinois electric utilities, Resources and Energy, 12, 383-398.
Färe, R. and D. Primont, 1990. A distance function approach to multioutput technologies, Southern Economic Journal, 56(4), 879-891.
Fecher, F. and S. Perelman, 1992, Productivity growth and technical efficiency in OECD industrial activities, in: R. Caves, eds., Industrial Efficiency in Six Nations (MIT Press, Cambridge Mass.).
Field, B.C. and Ch. Grebenstein, 1980, Capital-Energy Substitution in U.S. manufacturing, Review of Economics and Statistics 62(2): 207-212.
Fisher, I., 1922, The making of index numbers (Houghton Mifflin, Boston).
Fukuyama, H. and W.L. Weber, 1999, The efficiency and productivity of Japanese securities firms, 1988-1993, Japan and the World Economy, 11(1), 115-133.
Gabrielsen, A., 1975, On estimating efficient production functions, Working Paper no A-35, Chr. Michelsen Institute, Department of Humanities and Social Sciences, Bergen, Norway.
Greene, W.M., 1980, Maximum likelihood estimation of econometric frontier funtions, Journal of Econometrics 13(1): 27-56.
Grosskopf, D., and S. Self, 2001, Growth, human capital and TFP, Paper presented at the WEA meetings, San Francisco.
Gowdy, J.M., 1992, Labour productivity and energy intensity in Australia 1974-87, Energy Economics 14(1), 43-48.
Gullickson, W. and M.J. Harper, M.J., 1987, Multifactor productivity in US manufacturing, 1949-1983, Monthly Labor Review, 18-28.
Hisnanick, J.J. and B.L. Kyer, 1995, Assessing a disaggregated energy input using confidence intervals around translog elasticity estimates, Energy Economics 17(2): 125-132.
Hisnanick, J.J. and K.O. Kymm, 1992, The impact of disaggregated energy on productivity, Energy Economics 14(4), 274-278.
Hulten, CH.R., 2000, Total factor productivity: a short biography, NBER Working Papers, No. 7471, Department of economics, New York University.

Iqbal, M., 1986, Substitution of labor, capital and energy in the manufacturing sector of Pakistan, Empirical Economics 11, 81-95.
Jorgenson, D.W., 1983, Energy prices and productivity growth, in: S. Schurr, S. Sonenblum and D.O. Wood, eds., Energy, Productivity, and Economic Growth (Cambridge University Press, Cambridge, Mass.).
Jorgenson, D.W., 1984, The role of energy in productivity growth, The Energy Journal 5, 11-26.
Jorgenson, D.W., 1988a, Productivity and postwar U.S. economic growth, The Journal of Economic Perspectives 2(4), 23-41.
Jorgenson, D.W., 1988b, Productivity and economic growth in Japan and the United States, American Economic Review 78(2), 217-222.
Kendrick, J.W., 1961, Productivity trends in the United States (Princeton University Press, Princeton, New Jersey).
Kendrick, J.W., 1973, Postwar productivity trends in the United States, 1948-1969 (National Bureau of Economic Research, New York).
Kintis, A.A. and E.E. Panas, 1989, The capital-energy controversy: further results, Energy Economics 11(3): 201-212.
Lucas, R., 1988, On the mechanics of economic development, Journal of Monetary Economics 22(1), 3-42.
Kumbhakar, S.C., 1987. The specification of technical and allocative inefficiency of multi-product firms in stochastic production and profit frontiers. Journal of Quantitative Economics 3, 213-223.
Kumbhakar, S.C., 1990, Production frontiers, panel data and time-varying technical inefficiency. Journal of Econometrics 46(1/2), 201-211.
Lee, Y.H. and P. Schmidt, 1993, A production frontier model with flexible temporal variation in technical inefficiency, in: Harold O. Fried, C.A.K. Lovell y S.S. Schmidt eds., The Measurement of Productive Efficiency: Techniques and Applications, (Oxford :Oxford University Press), 237-255.
Malmquist, S., 1953, Index numbers and indifference curves, Trabajos de Estadística 4, 209-242.
Maudos, J., J.M. Pastor and L. Serrano, 1999, Total factor productivity measurement and human capital in OECD countries, Economics Letters 63, 39-44.
Meeusen, W. and J. van den Broeck, 1977, Efficiency estimation from Cobb-Douglas production functions with composed error, International Economic Review 18, 435-444.
Morrison, C.J. and E.R. Berndt, 1981, Short-run labor productivity in a dynamic model, Journal of Econometrics 16, 339-365.
Murillo-Zamorano, L.R., 2003, Economic efficiency and frontier techniques, Journal of Economic Surveys, forthcoming.
Murillo-Zamorano, L.R. and J.A. Vega-Cervera, 2001, The use of parametric and non-parametric frontier methods to measure the productive efficiency in the industrial sector. A comparative analysis, International Journal of Production Economics 69, 265-275.
Nadiri, M.I., 1970, Some approaches to the theory and measurement of total factor productivity: a survey, Journal of Economic Literature 8, 1137-1177.
Nishimizu, M. and J.M. Page, J.M., 1982, Total factor productivity growth, technological progress and technical efficiency change: dimensions of productivity change in Yugoslavia, 1967-1978, Economic Journal 92, 920-936.
Norsworthy, J.R. and D.H. Malmquist, 1983, Input measurement and productivity growth in Japanese and U.S. manufacturing, American Economic Review 73(5), 947-967.

OECD, 2001, Measuring productivity. OECD Manual. Measurement of aggregate and industry-level productivity growth. Paris.
Petraglia, C., 2003, Total factor productivity growth and public capital: the case of Italy, Estudi Economic, forthcoming.
Pindyck, R.S. and J.J. Rotemberg, 1983, Dynamic factor demands and the effects of energy price shocks, American Economic Review 73(5): 1066-1079.
Pitt, M.M. and L.F. Lee, 1981, The measurement and sources of technical inefficiency in the Indonesian weaving industry, Journal of Development Economics 9, 43-64.
Richmond, J., 1974, Estimating the efficiency of production. International Economic Review 15, 515-521.
Romer, P.M., 1986, Increasing returns and long run growth, Journal of Political Economy 94(5), 1002-1057.
Romer, P.M., 1989, Capital accumulation in the theory of long run growth, in: R.J. Barro eds., Modern Business Cycle Theory (Cambridge: Hardvard University Press).
Rosenberg, N., 1983. The effects of energy supply characteristics on technology and economic growth, in: S. Schurr, S. Sonenblum and D.O. Wood, eds., Energy, Productivity, and Economic Growth (Cambridge University Press, Cambridge, Mass.).
Schmidt, P., and R.C. Sickles, 1984. Production frontiers and panel data. Journal of Business and Economic Statistics, 2, 299-326.
Schurr, S., 1983, Energy efficiency and economic efficiency: an historical perspective, in: S. Schurr, S. Sonenblum and D.O. Wood, eds., Energy, Productivity, and Economic Growth (Cambridge University Press, Cambridge, Mass.).
Seiford, L.M. and R.M. Thrall, 1990, Recent development in DEA: the mathematical programming approach to frontier analysis, Journal of Econometrics 46, 7-38.
Shepard, R.W., 1970, Theory of cost and production function (Princeton University Press, Princeton, New Jersey).
Solow, R.W., 1957, Technical change and the aggregate production function, Review of Economic and Statistics 39, 312-320.
Summers, R. and A. Heston, A., 1991, The Penn World Table (Mark 5): an expanded set of international comparisons, 1950-1987, Quarterly Journal of Economics 106, 1-41.
Tornqvist, L., 1936, The Bank of Finland's consumption price index, Bank of Finland Monthly Bulletin 10, 1-8.
Vega-Cervera, J.A. and J.M. García-Hierro, 2000, Energy as a productive input: the underlying technology for Portugal and Spain, Energy 25(8): 757-775.
Watkins, G.C. and E.R. Berndt, 1991, Dynamic models of input demands: a comparison under different formulations of adjustment costs, in: J.R. Moroney (Eds.), Advances in the Economics of Energy and Resources, vol. 7 (Greenwich, CT: JAI Press): 161-190.
Yaisawarng, S. and J.D. Klein, 1994, The effects of sulfur dioxide controls on productivity change in the US electric power industry, Review of Economics and Statistics, 76(3), 447-460.

Tables

Table 1. TFP growth decomposition with and without energy factor. Average annual changes

	Without energy			With energy		
Country	Effch	Techch	Tfpch	Effch	Techch	Tfpch
Australia	0.998	1.008	1.006	0.995	1.011	1.006
Austria	0.992	0.996	0.988	0.996	1.009	1.005
Belgium	1.006	1.005	1.011	1.005	1.010	1.015
Canada	1.004	1.005	1.009	1.004	1.006	1.010
Denmark	0.998	0.996	0.994	0.995	1.016	1.011
Finland	1.011	1.007	1.017	1.007	1.011	1.018
France	0.999	1.003	1.002	1.001	1.011	1.013
Greece	1.005	0.993	0.998	0.988	1.004	0.991
Ireland	1.010	0.989	0.999	1.010	0.992	1.002
Italy	1.003	0.993	0.996	1.000	1.013	1.013
Japan	0.993	0.993	0.987	1.006	1.007	1.013
Luxembourg	1.008	1.008	1.017	1.008	1.009	1.017
Netherlands	0.997	0.997	0.995	0.996	1.006	1.001
Portugal	1.001	0.993	0.995	1.002	0.995	0.997
Spain	0.990	0.992	0.982	0.994	0.994	0.988
Sweden	0.995	1.004	0.998	0.996	1.010	1.006
UK	1.000	0.991	0.991	1.000	0.995	0.995
USA	1.000	1.000	1.000	1.000	1.003	1.003
Mean	1.001	0.999	0.999	1.000	1.006	1.006

Effch: Average annual changes for efficiency change. Techch: Average annual changes for technological progress. Tfpch: Average annual changes for TFP growth.

Table 2. Log-likelihood functions and generalized likelihood-ratio statistics

Models	Without energy (Restricted model)	With energy (Generalized model)	Generalized likelihood ratio
Model 1	Log L: 647.052	Log L: 0.675.418	LR=-2(647.052-675.418)=56.732 χ^2_1=6.63(99%)
Model 2	Log L: 603.299	Log L: 0.698.199	LR=-2(603.299-698.199)=189.8 χ^2_4=13.23(99%)

Model 1: Cobb-Douglas Truncated-Normal Time Variant Model. Model 2: Translog Truncated-Normal Time Variant Model.
Log L: Log likelihood function value. LR: Generalized likelihood-ratio statistic for testing the null hypothesis.

Table 3. Productivity, technology, efficiency, and energy

Models	Productivity/Energy	Technology/Energy
Fixed effects model N = 414	**0.0447** (1.962)	**0.1008** (5.181)
LM Test[1] *1 df*	*782.79* *Prob. value = 0.0000*	*923.21* *Prob. value = 0.0000*
Hausman Test[1] *1 df*	*14.97* *Prob. value = 0.0001*	*12.66* *Prob. value = 0.0003*
Random effects model N = 414	0.0241 (1.090)	0.0856 (28.995)
	Efficiency/Energy	
Censored tobit model N = 414	**0.0645** (7.963)	

[1] Large values of the Hausman statistic argue in favour of the fixed effects model over the random effects model. Large values of the Lagrange multiplier (LM) statistic argue in favour of one of one of the one factor models (fixed or random effects) against the classical regression with no group specific effects. Bold figures identify the statistically relevant models. T-ratios are given in parentheses.

Figures

Figure 1. Malmquist Productivity Indexes

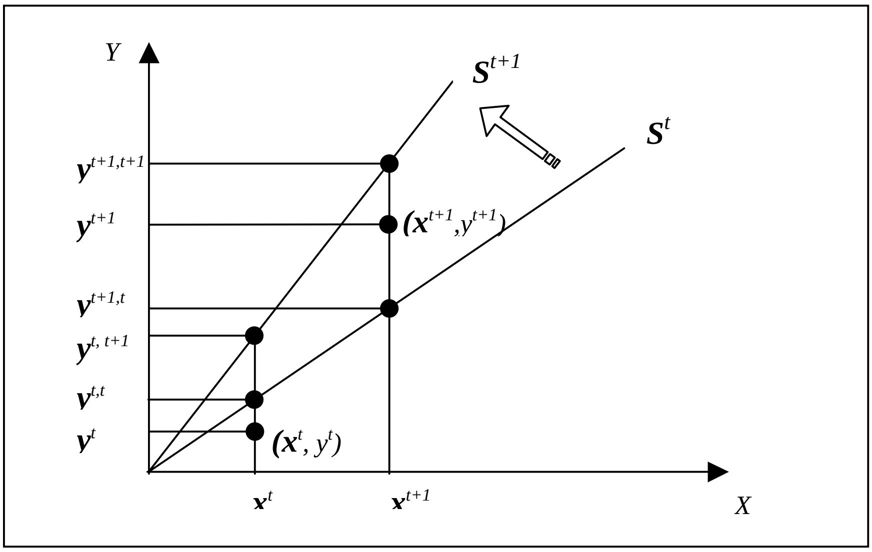


Figure 2. Productivity in OECD countries: 1970=100

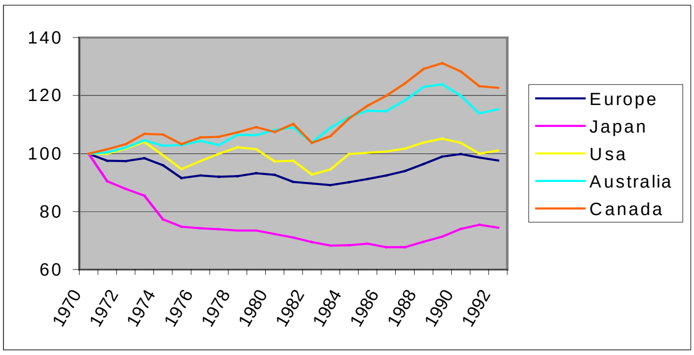


Figure 3. Technological progress in OECD countries: 1970=100

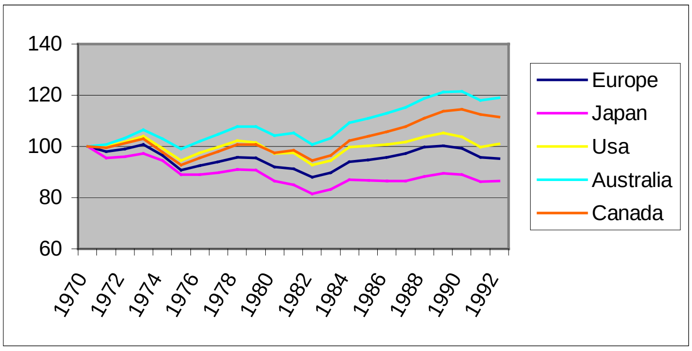


Figure 4. Technical efficiency in OECD countries: 1970=100

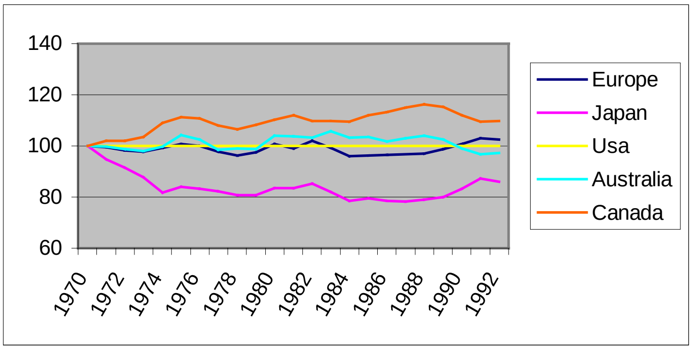


Figure 5. TFP growth average rates with (+) and without (-) energy

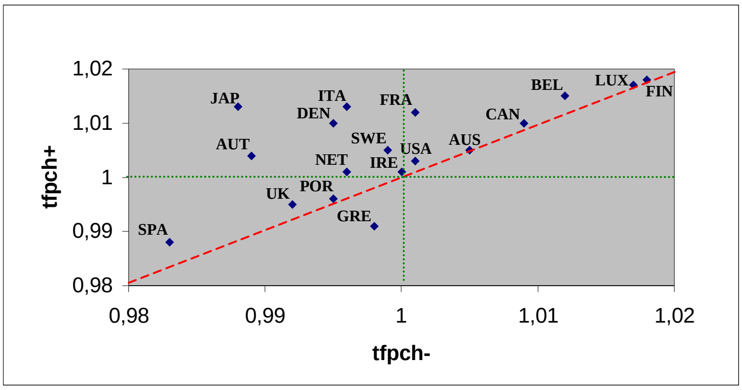


Figure 6. Technological progress average rates with (+) and without (-) energy

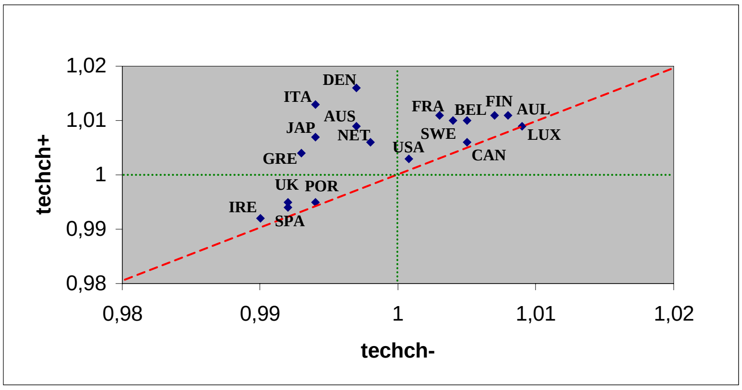


Figure 7. Technical efficiency change average rates with (+) and without energy (-)

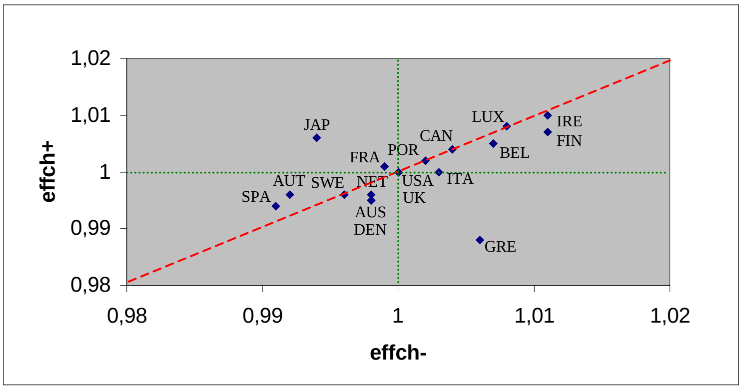


Figure 8. Productivity in OECD countries: 1970=100

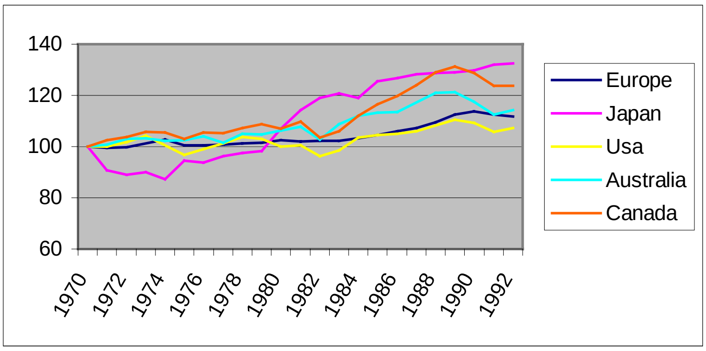


Figure 9. Technological progress in OECD countries: 1970=100

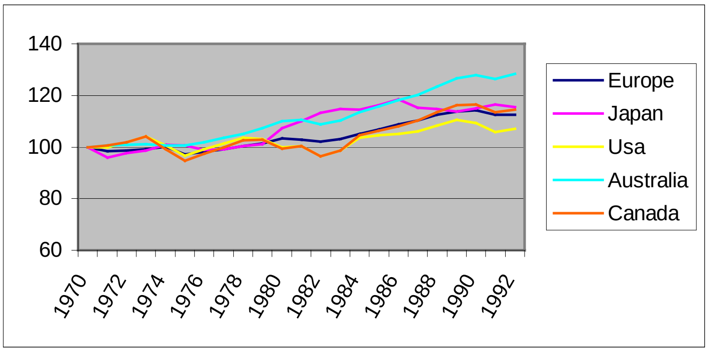
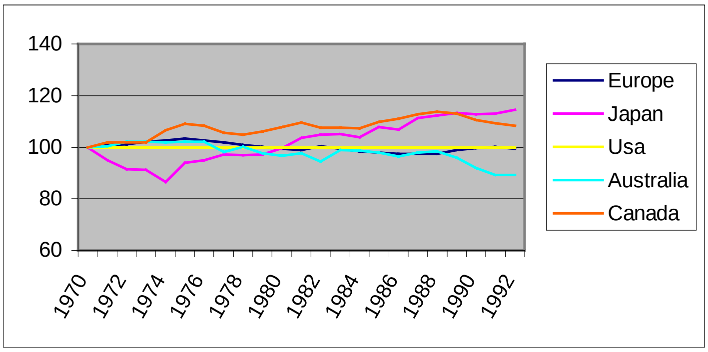


Figure 10. Technical efficiency in OECD countries: 1970=100



APPENDIX

The model

The measurement of productive efficiency by means of parametric techniques requires the specification of a particular frontier function. Such specification can be either deterministic or stochastic. Deterministic models envelope all the observations, identifying the distance between the observed production and the maximum production, defined by the frontier and the available technology, as economic inefficiency. On the other hand, stochastic approaches permit one to distinguish between technical inefficiency and statistical noise.

Several techniques have been developed in the econometric literature to estimate both deterministic[32] and stochastic frontier models. Aigner, Lovell and Schmidt (1977), Meeusen and van den Broeck (1977), and Battese and Corra (1977) simultaneously developed a stochastic frontier model that, besides incorporating the efficiency term into the analysis (as do the deterministic approaches), also captures the effects of exogenous shocks beyond the control of the analysed units. Moreover, this type of model also covers errors in the observations and in the measurement of outputs. These initial approaches were developed within a cross-section framework and based on strong distribution assumptions for modeling the inefficiency effect.

However, if panel data are available, there is no need for any distribution assumption for the inefficiency effect, and all the relevant parameters of the frontier technology can be obtained by simply using the traditional estimation procedures for panel data, i.e. the fixed-effects and the random-effects model approaches. This was first noted by Schmidt and Sickles (1984).

In any case, when the distribution assumptions involved in both the specification and the estimation of stochastic frontier functions are known, similar maximum likelihood techniques to the ones applied to the cross-sectional data can be applied to a stochastic production frontier panel data model in order to get more efficient estimates

[32] Modified Ordinary Least Squares (e.g. Richmond, 1974), Corrected Ordinary Least Squares (e.g. Gabrielsen, 1975), and Maximum Likelihood Estimation (e.g. Greene, 1980) are some of the most important.

of the parameter vector and of the technical inefficiency scores. In this respect, Pit and Lee (1981) derived the normal-half-normal counterpart of Aigner, Lovell and Schmidt's (1977) model for panel data, while Kumbhakar (1987) and Battese and Coelli (1988) extend Pitt and Lee's (1981) analysis to the normal-truncated stochastic frontier panel data model. Maximum likelihood techniques are also applied to unbalanced panel data in Battese, Coelli and Colby (1989).

Both the fixed/random-effects approaches and maximum likelihood techniques considered technical inefficiency effects to be time-invariant. However, as the time dimension becomes larger, it seems more reasonable to allow inefficiency to vary over time. As with the time-invariant technical inefficiency model, time-varying technical inefficiency can be estimated by using either fixed or random effects or maximum likelihood techniques. Cornwell, Schmidt and Sickles (1990) and Lee and Schmidt (1993) are examples of the former; Kumbhakar (1990) and Battese and Coelli (1992) of the latter.

Following Battese and Coelli's (1992) approach, we next specify two alternative functional forms for the productive technology of the industrialized countries under analysis, namely a Cobb-Douglas (Model 1) and a translog (Model 2) stochastic production function.

Model 1: Cobb-Douglas Truncated-Normal Time-Variant Model

$$\ln y_i^t = \beta_0 + \sum_{m=1}^{M} \beta_m \ln x_{mi}^t + v_i^t - u_i^t$$

$$v_i^t \approx N(0,\sigma^2) \qquad u_i^t = \delta(t)u_i = \left[\exp(-\eta(t-T)\right]u_i$$

$$i = 1,\dots K; m = 1,\dots M; t = 1,\dots T$$

Model 2: Translog Truncated-Normal Time-Variant Model

$$\ln y_i^t = \beta_0 + \sum_{m=1}^{M} \beta_m \ln x_{mi}^t + \sum_{m\leq}^{M}\sum_{n=1}^{M} \beta_{mn} \ln x_{mi}^t \ln x_{ni}^t + v_i^t - u_i^t$$

$$v_i^t \approx N(0,\sigma^2) \qquad u_i^t = \delta(t)u_i = \left[\exp(-\eta(t-T)\right]u_i$$

$$i = 1,\dots K; m,n = 1,\dots M; t = 1,\dots T$$

In these models, $i = 1,...K$ indicates the units, $m, n = 1,...M$ indicate the inputs, y_i^t is the output, and x_{mi}^t are productive factors. The term $v_i^t - u_i^t$ is a composed error term where v_i^t represents randomness (or statistical noise) and u_i^t represents technical inefficiency. The error representing statistical noise is assumed to be independent and identically distributed (i.i.d.) as a normal random variable. With respect to the one-sided (inefficiency) error term it is specified as an exponential function of time and assumed to be i.i.d. as the generalized truncated-normal random variable. The parameter η is an unknown scalar parameter to be estimated.

Hypothesis test

For the stochastic frontier models specified above, the null hypothesis that the energy factor is not relevant within the technology of the OECD countries under analysis can be subjected to a generalized likelihood-ratio test. This test requires the estimation of the model under both the null (H_0) and alternate (H_1) hypotheses. The test statistic is calculated as

$$LR = -2\{\ln[L(H_0)/L(H_1)]\}=-2\{\ln[L(H_0)]-\ln[L(H_1)]\}$$

Where $L(H_0)$ and $L(H_1)$ are the values of the likelihood function under the null and alternative hypotheses, H_0 and H_1, respectively. If H_0 is true, this test statistic is usually assumed to be asymptotically distributed as a chi-squared random variable with degrees of freedom equal to the number of restrictions involved (in this instance one for Model 1 and four for Model 2).

The output file[33] for estimating the Cobb-Douglas model using FRONTIER[34] software gives a value for the log-likelihood function under the null hypothesis of 647.052, and 675.418 under the alternate hypothesis. As a result, the value of the

[33] The output file is not presented here to save space. A full set of results is available on request.

[34] FRONTIER program (Coelli, 1996a) automate the maximum likelihood method for estimation of the parameters of stochastic frontier models. This program uses a three-step estimation procedure. The first step involves calculation of the OLS estimators. In the second step, the likelihood function is evaluated for a number of alternative scenarios in terms of contribution of the inefficiency term to the total variance of the model. In the final step, the program uses best estimates from the second step as starting values in a Davidon-Fletcher-Powell iterative maximization routine which obtains the maximum likelihood estimates when the likelihood function attains its global maximum.

generalized likelihood-ratio statistic for testing the null hypothesis is calculated to be 56.732. This value is compared with the upper one-per-cent point for the χ^2_1 distribution, which is 6.63. Thus the null hypothesis that energy input is not relevant within the underlying productive technology is rejected. With respect to the translog model, the values for the log-likelihood function under the null and alternate hypothesis are 603.299 and 698.199, respectively. This yields a generalized likelihood-ratio statistic of 189.8. After comparing this value with the upper one-pe-cent point for the χ^2_4 distribution (13.23), the null hypothesis that energy input is not relevant within the underlying productive technology is rejected once again.